MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, Jan-June 2026, Pages: 806-823

Labor Productivity in a Developing Economy: A Case Study of Vietnam

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Abstract

Vietnam is transitioning toward a productivity-driven growth model. This study evaluates the effects of four structural factors, namely sectoral transformation, gross capital formation, foreign direct investment, and the services sector, on labor productivity from 1990 to 2023. Using time series data, the analysis employs three quantitative methods, including the Autoregressive Distributed Lag model, the Quantile-on-Quantile Regression, and the Bayesian Time Varying Coefficient VAR model. The results indicate that structural transformation and foreign direct investment exert significant positive effects on labor productivity, particularly in low and medium productivity groups. Conversely, gross capital formation and the services sector display negative or unstable effects, suggesting inefficiencies in investment and service quality. The Bayesian TVC VAR model further reveals that structural transformation is the only factor with a stable long-time influence. These findings highlight the importance of shifting labor toward higher value-added industries, strengthening technological absorption, and modernizing services to sustain productivity growth. The study contributes new empirical evidence and an integrated methodological approach that elucidates heterogeneous effects across different productivity levels and time-varying impacts of productivity determinants in a developing economy.

Keywords: Labor productivity; ARDL; QQR; Bayesian TVC-VAR, Vietnam.

Introduction

Labor productivity is a fundamental driver of long-term economic growth, rising incomes, and national competitiveness (Mikhnenko, 2021). As Vietnamese transitions toward a productivity- and efficiency-based growth model, understanding the determinants of labour productivity becomes increasingly critical (Khang, 2025; Thang et al., 2025). Between 2007 and 2019, Vietnam's labor productivity increased by 69.83%, with pure productivity gains contributing 36.74% and structural transformation 24.20%. This highlights the dual importance of within-sector efficiency improvements and cross-sector labor reallocation in driving aggregate productivity growth (Oh & Kang, 2022). Evidence from manufacturing further shows that shifting labor from low- to high-productivity enterprises significantly enhance productivity (Khac Minh et al., 2019). Moreover, innovation, skill upgrading, and technological adoption are emerging as key drivers of productivity growth (Duong, 2019).

Despite notable progress, Vietnam's labor productivity continues to face structural challenges. Inefficient labor allocation across regions and enterprise types, uneven technological adoption, and disparities in ownership structures constrain efficiency (Nguyen et al., 2022). The ability of domestic firms to absorb technology from foreign direct investment (FDI) is particularly decisive (Tran et al., 2024), while FDI, exports, and capital goods imports exert positive long-term effects on productivity (Asada, 2020). Market barriers and weal policy coordination further hinder productivity growth (Ayerst et al., 2020). Labor rellocation from agriculture to industry and services, especially in dynamic regions such as the Red River Delta, also contributes to productivity gains (Ayerst et al., 2024).

Overall, these findings indicate that Vietnam's productivity performance depends not only on traditional factors such as investment or labor structure, but also on technological absorption capacity, market development, and policy coherence. Accordingly, this study examines the effects of structural transformation, investment, FDI, and service-sector development on labor productivity using three complementary econometric techniques, including Autoregressive Distributed Lag (ARDL), Quantile-on-Quantile Regression (QQR), and Bayesian Time-Varying Coefficient Vector Autoregression (Bayesian TVC-VAR). The integrated analysis aims to identify short- and long-term dynamics, providing evidence-based insights to optimize investment strategies, accelerate economic restructuring, bolster innovation, and sustain high-quality productivity growth in Vietnam.

Literature review

Theoretical background on labor productivity

Endogenous growth theory posits that labor productivity is driven by physical capital, knowledge, and technology generated by economic agents (Romer, 1990). Key to long-term growth are investments in R&D, a skill workforce, and technological diffusion. Zamparelli (2024) emphasizes the role of targeted technological innovation and the R&D structures in boosting productivity. Zhao et al. (2025) highlights how digital M&A activities improve productivity by enhancing innovation efficiency and reducing organizational uncertainty. These studies emphasize the influence of FDI, investment, manufacturing growth, and economic structure on productivity.

Structural transformation theory (Lewis, 1954) suggests that moving labor from agriculture to industry and services increases productivity, known as the "shift effect". Naveed & Wang (2023) argue that technology enhances productivity only when accompanied by labor shifts to higher-value sectors. Emako et al. (2022) further note that FDI generates horizontal and vertical spillovers, restructuring labor and boosting domestic productivity.

Kuznets (1973) links productivity to capital, technology, and industrial structure changes, while Yuan et al., (2010) illustrate how production structure influences the productivity gap between China and the U.S. Satchi & Temple (2009) emphasizes institutional barriers that impede labor reallocation, and Moon & Lee (2013) demonstrate that agriculture remain vital in Asia. AlKathiri (2022) argues that capital accumulation is the primary driver of productivity in manufacturing, though technical efficiency tends to decline over time.

In sum, research from endogenous growth theory and structural transformation theory, alongside empirical studies, shows that labor productivity results from the interaction between technological innovation, industrial structure, and resource reallocation capacity. FDI, investment, and structural transformation not only affect productivity but also amplify each other's impact when coordinated within the right institutional and technological context. This study develops a model to quantify the combined effects of these factors on labor productivity in Vietnam.

Overview of influencing factors

Table 1 summarizes key studies on labor productivity and its determinants. Labor productivity, measured as Gross Domestic Product (GDP) per person employed, reflects resource use efficiency and economic growth quality, aligning with Uzyakov & Uzyakova's (2025) framework for assessing the economy's capacity to absorb capital and technology. Productivity is also influenced by factors like informal employment (Uzyakova, 2022) and regional or sectoral disparities (Zhang et al., 2022), highlighting the importance of structural factors such as FDI, investment, and structural transformation, which are key channels for technology spillovers and productivity growth in developing countries (Emako et al., 2022; Saha, 2024).

Gross Capital Formation (GCF) represents physical investment's role in expanding production capacity and labor efficiency. GCF not only directly impacts productivity but is also shaped by factors like demographic structure and globalization (Choudhry et al., 2016; Z. Zhao et al., 2024). Capital accumulation is recognized as a major driver of productivity growth, especially in economies with limited investments, such as Vietnam (Ali & Akhtar, 2024; Sasmal & Sasmal, 2023). However, its effectiveness depends on the quality of allocation and alignment with technological innovation (Chen & Wu, 2024), misallocation can lead to inefficiency (Chen & Wu, 2024; Y. Yao et al., 2024). Thus, including GCF into the model is crucial for evaluating investment's role in productivity enhancement.

FDI is included to capture its role in improving productivity through technology spillovers and industrial restructuring (Piscitello & Rabbiosi, 2005). Studies confirm that FDI positively impacts productivity, particularly in countries catching up with higher development levels, especially when combined with exports or strategic investment (Ali & Akhtar, 2024; Fillat & Woerz, 2011). However, FDI's effectiveness is contingent on labor quality and institutional context (Bacovic et al., 2021), making it important to assess both its direct and indirect effects on productivity in developing economies (Yang, 2024).

The services sector (SERV) is included to examine its structural role and potential contribution to productivity. Many studies show that services have become a key driver of growth, particularly when combined with technology and knowledge (Broersma & Ark, 2007; Kinfemichael, 2019). Sectors such as finance, transportation, and telecommunications significantly influence productivity (Sauian et al., 2013), and productivity in complex service roles can remain stable or increase with age (Börsch-Supan et al., 2021). Including SERV helps clarify the role of services in economic modernization and labor efficiency (Thakur, 2023).

Integrated approach to labor productivity research

Recent studies show that labor productivity is positively influenced by GCF, FDI, technological innovation, and the services sector, while informal employment and regional disparities hinder efficiency. However, traditional methods like Fixed Effects, Panel GMM, or VAR have limitations in capturing nonlinear and asymmetric effects across productivity groups. Quantile Regression (QR) has proven effective in detecting such variations, as demonstrated in srtudies on trade, mechanization, and ICT (et al., 2025).

To address these gaps, this study combines ARDL to test linear relationships, QQR to analyze nonlinear and asymmetric effects, and Bayesian TVC-VAR to assess time-varying impacts, offering a more comprehensive approach to Vietnam's data. Additionally, the study revisits classical theories such as endogenous growth (Romer, 1990) and structural transformation (Kuznets, 1973; Lewis, 1954) within Vietnamese context, where FDI, public investment, and the services sector have shown inconsistent results. The insights gained will contribute to theoretical refinements better suited to the unique dynamics of developing economies.

Table 1. *A comprehensive review of previous research on labor productivity and its determinants*

No.	Variables	Econometric models	Study period	Country	Authors
1	FDI, Labor productivity	FDI through M&A impact	1994–1997	Italy	Piscitello & Rabbiosi (2005)
2	Manufacturing productivity, Labor quality	Labor quality index on industry productivity	2000s	Taiwan	San et al. (2008)
3	FDI, Industry-level labor productivity	Industry-level FDI effect by country stage	1987–2002	OECD, Asia, Eastern Europe	Fillat & Woerz (2011)
4	Innovation, Labor productivity (Service and Manufacturing)	Crépon-Duguet-Mairesse model	N/A	Colombia	Gallego et al. (2015)
5	Gross Capital Formation, Age dependency, Labor productivity	Panel fixed effects with interaction	1980–2010	Global	Choudhry et al. (2016)
6	FDI, Labor productivity	VAR shock to FDI determinants	2000s	Balkan countries	Bacovic et al. (2021)
7	Informal employment, Labor productivity	Structural factors of employment and productivity	N/A	Russia	Uzyakova (2022)
8	Labor productivity (regional dispersion)	Spatial productivity disparity analysis	2006–2018	China	Zhang et al. (2022)
9	FDI, Labor productivity	FDI spillover and structural transformation	1990–2018	Developing countries	Emako et al. (2022)
10	FDI, Labor productivity, PCI	Dynamic panel threshold analysis	2000–2018	88 countries	Saha (2024)
11	GCF, Financial globalization, TFP	Panel GMM estimation	1984–2019	20 emerging economies	Zhao et al., 2024)
12	FDI, Capital, Labor, TFP	OLS with Tornqvist TFP index	1991–2021	Pakistan	Ali & Akhtar (2024)
13	Intelligent manufacturing, Labor productivity	RBV, DID estimation	2010–2020	China	Zhu et al. (2024)
14	Integration manufacturing-services, Labor productivity	Forward/backward integration on productivity	2002, 2007, 2012, 2017.	China	Yao et al. (2024)
15	Labor productivity	Long-term productivity and labor constraints	N/A	EAEU countries	Uzyakov & Uzyakova (2025)

Methodology

Autoregressive Distributed Lag (ARDL) Method

The ARDL model, developed by Pesaran & Shin (1999), is designed to test and estimate cointegration relationships among time series variables with mixed integration orders (I(0) and I(1)). Unlike Johansen's or Engle–Granger's methods, ARDL is effective in small samples and allows for variable-specific lags structures. It does not require all variables to share the same integration order, making it highly flexible for empirical macroeconomic analysis. By reparametering ARDL into an Error Correction Model (ECM)(Engle & Granger, 1987; Johansen, 1988; Phillips & Ouliaris, 1990), the framework separates short-run dynamics from long-run equilibrium relationships, enabling a comprehensive assessment of both immediate and persistent effects.

The general ARDL estimation equation can be expressed as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=0}^{q} \theta_j X_{t-j} + \varepsilon_t$$

Where: Y_t denotes the dependent variable at time t, determined by its own lags and and the current and lagged values of the explanatory variables X. α_0 is the constant term; ϕ_i are coefficients of lagged Y_t, measuring the dynamic effect of past values; andθ_j are coefficients of lagged X, reflecting both current and delayed impacts of X on Y. X_{t-j} denotes explanatory variables lagged from 0 to q; ε_t is the error term; p and q are the maximum lag orders for Y and X, respectively. Lag lengths are selected automatically in Eviews using AIC or SIC criteria, following Nsor-Ambala & Amewu (2022). The residual ε_t are assumed to be Independent and Identically Distributed (IID) with zero mean and constant variance, σ^2_ε. The general ARDL specification can thus be decomposed into short-run and long-run components:

- General Long-Run Estimation Model:

$$Y_{t-1}^{\text{long run}} = \gamma_0 + \gamma_1 X_{t-1} + u_t$$

Where $\gamma_1 \frac{\sum \theta_j}{1-\sum \phi_i}$, represents the long-run coefficient.

- General Short-Run Estimation Model (ECM Form):

$$\Delta Y_t = \alpha + \lambda\, EC_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta Y_{t-i} + \sum_{j=0}^{q-1} \theta_j\, \Delta X_{t-j} + \varepsilon_t$$

Where Δ denotes the first-difference operator, capturing short-run changes ($\Delta Y_t = Y_t - Y_{t-1}$); EC_{t-1} is the error-correction term derived from the long-run equation ($EC_{t-1} = Y_{t-1} - Y_{t-1}^{\text{long-run}}$); λ represents the adjustment coefficient reflecting the speed of convergence to equilibrium; and $\theta_j^{(k)}$ are the short-run dynamic coefficients. The ECM is specified as follow:

$$\Delta LP_t = \alpha + \lambda\, EC_{t-1} \sum_{i=1}^{p-1} \delta_i \Delta LP_{t-i} + \sum_{j=0}^{q_1-1} \theta_j^{(1)} \Delta SHIFT_{t-j} + \sum_{j=0}^{q_2-1} \theta_j^{(2)} \Delta GCF_{t-j} + \sum_{j=0}^{q_3-1} \theta_j^{(3)} \Delta FDI_{t-j} + \sum_{j=0}^{q_4-1} \theta_j^{(4)} \Delta SERV_{t-j} + \varepsilon_t$$

The ARDL model is used to examine the relationship between labor productivity (LP) and factors including SHIFT, GCF, FDI, and SERV.

$$\Delta LP_t = \alpha + \underbrace{\lambda(LP_{t-1} - \gamma_1 SHIFT_{t-1} - \gamma_2 GCF_{t-1} - \gamma_3 FDI_{t-1} - \gamma_4 SERV_{t-1})}_{Long-run\ Component\ (ECM\ Form)} + \underbrace{\sum_{i=1}^{p-1} \delta_i \Delta LP_t - i}_{Short-run\ impact\ of\ LP}$$
$$+ \underbrace{\sum_{j=0}^{q_1-1} \theta_j^{(1)} \Delta SHIFT_{t-j}}_{Short-run\ impact\ of\ SHIFT} + \underbrace{\sum_{j=0}^{q_2-1} \theta_j^{(2)} \Delta GCF_{t-j}}_{Short-run\ impact\ of\ GCF} + \underbrace{\sum_{j=0}^{q_3-1} \theta_j^{(3)} \Delta FDI_{t-j}}_{Short-run\ impact\ of\ FDI} + \underbrace{\sum_{j=0}^{q_4-1} \theta_j^{(4)} \Delta SERV_{t-j}}_{Short-run\ impact\ of\ SERV} + \varepsilon_t$$

Where α is the constant in the short-run model, λ is the adjustment coefficient to long-run equilibrium (indicating cointegration if $\lambda < 0$ and statistically significant), and $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ are the long-run coefficients for SHIFT, GCF, FDI and SERV respectively. δ_i represents the lag coefficient of the dependent variable LP, and $\theta_j^{(k)}$are the short-run coefficients for the independent variables (k = 1, 2, 3, 4). ε_t is the random error term. The long-run equilibrium equation is:

$$LP_{t-1} == \gamma_1 SHIFT_{t-1} - \gamma_2 GCF_{t-1} - \gamma_3 FDI_{t-1} - \gamma_4 SERV_{t-1} + u_t$$

Before estimating the ARDL model, the stationarity of variables must be tested using the Augmented Dickey-Fuller (ADF) or Phillips-Perron (PP) tests to ensure none are I(2), as ARDL requires all variables to be I(0) or I(1) (Dickey & Fuller, 1979; Phillips & Perron, 1988). The Bounds Test is then applied to check for cointegration (Pesaran & Shin, 1999), where the F-statistic's position relative to the bounds to test whether cointegration exists. Model adequacy is assessed using the Breusch–Godfrey test (serial correlation), the White test (heteroskedasticity), and the Jarque–Bera test (normality of residuals).

Quantile-on-Quantile Regression Method

The QQR method, proposed by Sim & Zhou (2015), enables analysis of interactions between the quantiles of two variables, capturing nonlinear and asymmetric relationships often missed by ordinary linear or standard quantile regression (Qureshi et al., 2020). Like traditional quantile regression, QQR does not assum normality or homoskedasticity, making it suited for skewed or volatile economic data (Sim & Zhou, 2015).

In the conventional quantile regression (QR) model at quantile τ:

$$Y_t = \alpha(\tau) + \beta(\tau) X_{t-j} + \varepsilon_t^{\tau}$$

The effect of X_t on the τ^{th} quantile of Y_t is estimated without considering the quantile of X_t itself.

Building on this framework, the extended QQR model (Sim & Zhou, 2015) examines the relationship between labor productivity ($LnLP_t$) and each independent variable X_t (including $SHIFT_t, GCF_t, FDI_t, SERV_t$) across quantile pairs (θ, τ):

$$y_t^{\tau} = \beta_1^{(X)}(\tau, \theta) + \beta_2^{(X)}(\tau, \theta)\left(X_t - x_t^{\theta}\right) + \varepsilon_t^{(\theta,\tau)}$$

Where y_t^{τ} and x_t^{θ} denotes the $\tau -$ th quantile and $\theta -$ thquantile of $LnLP_t$ and X_t, respectively, and $\beta_2^{(X)}(\tau, \theta)$ measures the effect of the $\theta -$quantile of X_t on the $\tau -$ quantile of $LnLP_t$:

The Kernel-weighted quantile regression model is defined as:

$$\hat{\beta}(\tau, \theta) = agr \min_{\beta(\tau,\theta)} \sum_{t=1}^{T} \rho_{\tau}\left(y_t - \beta_1(\tau, \theta) - \beta_2(\tau, \theta)\left(x_t - x_t^{\theta}\right)\right) K\left(\frac{x_t - x_t^{\theta}}{h}\right)$$

Where $\rho_{\tau}(u) = u\left(\tau - I(u < 0)\right)$ is the check function, and $K(\cdot)$ is the Kernel function assigning weights to near observations.

This study employs the Gaussian Kernel:

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
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$$K(u) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{u^2}{2})$$

Where $u = \frac{x_t - x_t^{\theta}}{h}$ and h is the bandwidth, determined using Silverman's rule (Silverman, 1998):

$$h = 0.9.\min\left(\sigma, \frac{IQR}{1.34}\right).n^{\frac{-1}{5}}$$

Where σ is the sample standard deviation, IQR is the interquartile range, and n is the observation number.

The Gaussian Kernel is chosen for its smothness and continuity across the entire domain, while the Epanechnikov kernel is also considered for its theoretically optimal in some nonparametric settings (Epanechnikov, 1969):

$K(u) = \frac{3}{4}(1 - u^2)$ với $|u| \leq 1$

Both Kernel and Silverman's bandwidth selection rule ensure optimal smoothing and estimated quality in nonlinear analysis such as QQR.

Bayesian TVC-VAR method

In macroeconomics, the relationships between variables often evolve due to policy changes, economic events, or structural transformation. The Bayesian TVC-VAR method, developed by Koop & Korobilis (2009) and Primiceri (2005), captures this dynamic feature by allowing regression coefficients to vary over time, unlike the fixed coefficients in traditional VAR model. This approach combines the Kalman filter with Bayesian estimation to efficiently handle small samples and high volatility, while controlling for uncertainty.

The general Bayesian TVC-VAR model consists two key equations: the measurement equation and the state equation:

$$y_t = X_t' \beta_t + \varepsilon_t$$
$$\beta_t = \beta_{t-1} + u_t$$

Where y_t is the vector of variables at time t, X_t' is the matrix of lagged variables, β_t is the time-varying coefficient vector, $\varepsilon_t \sim \mathcal{N}(0, \Sigma)$; $u_t \sim \mathcal{N}(0, Q)$.

For this study, the empirical model includes labor productivity (LP), structural shift (SHIFT) and capital accumulation (GCF). The specific application equation is:

$$\begin{cases} (LP_t, SHIFT_t, GCF_t, FDI_t, SERV_t)' = (I_5 \otimes Z_t')\beta_t + \varepsilon_t \\ \beta_t = \beta_{t-1} + u_t \end{cases}$$

Where Z_t' includes the appropriate lags of the variables, and I_5 is a 3x3 identity matrix.

The Bayesian estimation procedure follows these steps: (i) specify prior distributions for β_0, Σ, Q; (ii) apply the Kalman filter to update β_t at each time step; and (iii) use Gibbs sampling or the Metropolis–Hastings algorithm to draw posterior samples of the model parameters (Cogley & Sargent, 2005; Primiceri, 2005).

The Bayesian TVC-VAR offers several advantages over traditional VAR: it allows coefficients to adapt over time, reflecting evolving economic conditions (Primiceri, 2005); it works well with short- to medium-length time series by incorporating prior information (Koop & Korobilis, 2009); and it can identify structural changes without pre-specifying their timing or mechanisms (Cogley & Sargent, 2005). Given these benefits, the Bayesian TVC-VAR model is well-suited for analyzing the Vietnamese economy.

Data collection

This study utilizes annual time-series data from 1987 to 2023 (36 observations), ensuring that the number of observations exceeds the number of variables by more than 20, as recommended by Tabachnick & Fidell (2007) and Pham et al., (2022). The model incorporates the following variables:

- Labor Productivity (LP): Measured as GDP per person employed (constant 2021 PPP $), reflecting labor efficiency and economic growth quality.
- Structural Shift (SHIFT): The difference between the share of industry and agriculture in GDP, indicating industrialization and resource reallocation across sectors.
- Gross Capital Formation (GCF): Expressed as a percentage of GDP, GCF indicates investment capacity, crucial for long-term economic growth.
- Foreign Direct Investment (FDI): The ratio of GDP, capturing economic openness and potential technology spillovers.
- Services Sector (SERV): This value added by the services sector as a percentage of GDP, representing the shift towards a more modern, service-driven economy.

Descriptive statistics for these variables, including the mean, median, standard deviation, skewness, kurtosis, and the range of values, are summarized in Table 2, offering insihts into their distribution and variability over the study period.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, Jan-June 2026, Pages: 806-823

Table 2. *Descriptive statistics of the variables*

Indicator	LP (Labor Productivity– GDP per person employed, constant 2021 PPP $)	SHIFT (Structural Shift – difference between the share of Industry and Agriculture in GDP)	GCF (Gross Capital Formation, % GDP)	FDI	SERV (% GDP)
Mean	12709.38	11.16	32.3	4.98	40.26
Median	11834.03	17.65	32.02	4.36	41.26
Standard deviation	5433.52	13.999	3.04	2.55	3.23
Kurtosis	-0.6	0.14	-0.04	1.1	3.18
Skewness	-0.64	-1.13	0.42	0.54	-1.69
Minimum	5409.08	-22.33	27.14	0.03	29.74
Maximum	24236.15	26.22	39.57	11.94	44.06
Observations	33	37	29	37	37

Result

ARDL model results

Unit Root test and Cointegration test

The study applies the ADF and PP tests to assess the stationary of the data series. The results (Table 3) show that all variables, including lnLP, SHIFT, GCF, FDI, and SERV, are stationary after first difference, meaning they are I(1). No variable is I(2), satisfying the conditions for the ARDL model and enabling the analysis of both long-term and short-term relationships.

Table 3. *Unit Root test*

Null hypothesis (H_0): The variable has a unit root (non-stationary)

Variable	Model	ADF		PP		Order of integration (with constant)
		At level	At first difference	At level	At first difference	
LnLP	Constant	-0.7923 ns	-3.4264 **	-0.6406 ns	-3.3729 **	I(1)
	Trend	-2.2643 ns	-3.3669 *	-2.0900 ns	-3.3136 *	
	None	17.2425 ns	-0.8215 ns	12.3081 ns	-1.0523 ns	
SHIFT	Constant	-1.3765 ns	-7.2032 ***	-1.3802 ns	-6.8453 ***	I(1)
	Trend	-1.1885 ns	-8.3945 ***	-1.2133 ns	-8.9468 ***	
	None	0.2233 ns	-5.7730 ***	-0.0891 ns	-5.7667 ***	
GCF	Constant	-2.1111 ns	-5.0049 ***	-2.1329 ns	-5.0048 ***	I(1)
	Trend	-1.8504 ns	-5.0737 ***	-1.8560 ns	-5.0728 ***	
	None	0.3150 ns	-5.0748 ***	0.3292 ns	-5.0748 ***	
FDI	Constant	-2.6595 *	-5.1132 ***	-2.6595 *	-5.1132 ***	I(0); I(1)
	Trend	-2.4884 ns	-5.1893 ***	-2.4884 ns	-5.1893 ***	
	None	-0.8129 ns	-5.1654 ***	-0.8129 ns	-5.1654 ***	
SERV	Constant	-3.4776 **	-3.6867 ***	-3.1535 **	-5.3014 ***	I(0); I(1)
	Trend	-6.4267 ***	-3.5068 *	-2.8992 ns	-5.5077 ***	
	None	0.6113 ns	-3.3016 ***	0.7665 ns	-5.1864 ***	

*Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Unit root tests: ADF and PP.*

The Bounds test results (Table 4) shown an F-statistic of 40.5844, well above the critical bounds at all significance levels, leading to the rejection of the null hypothesis (H_0) and confirming a long-run relationship between LP and GCF, FDI, SHIFT, and SERV. This cointegration validates the ARDL estimates and underscores the long-term importance of structural transformation, investment, and the services sector in driving labor productivity, providing key empirical evidence for Vietnam's ongoing economic integration and transformation.

Table 4. *Bounds Test Estimates in the ARDL model*

Null hypothesis (H_0): No cointegration relationship exists (at level)

F-statistic	Critical Value Bounds for the Bounds Test		
	Significance level	I(0)	I(1)
40.5844	10%	2.752	3.994
	5%	3.354	4.774
	1%	4.768	6.67

Short-Run and Long-Run relationships

Table 5 presents the ARDL (3,3,3,3,3) model results with LnLP as the dependent variable. The error correction term (ECT) is negative and significant at the 1% level (–0.3651; $p < 0.01$), indicating a long-run cointegration relationship and 36.5% annual speed of adjustment toward equilibrium after a shock.

In the long run, SHIFT has a positive effect on LP ($\beta = 0.1485$; $p<0.01$), with FDI showing the largest positive impact ($\beta = 0.4900$; $p<0.01$). Conversely, GCF ($\beta = –0.0838$; $p<0.01$) and SERV ($\beta = –0.1998$; $p<0.01$) exhibit negative long-run effects.

In the short run, the first differences of SHIFT, FDI, and SERV are significant at the 1% level, indicating immediate effects of LP. Notably, ΔFDI shows a bidirectional effect, with a positive coefficient at lag 1 ($\beta = 0.0657$) and a negative coefficient at lag 2 ($\beta = –0.0872$), both significant. ΔSERV at lag 2 maintains a positively significant effect ($\beta = 0.0205$; $p<0.01$), despite its long run negative effect.

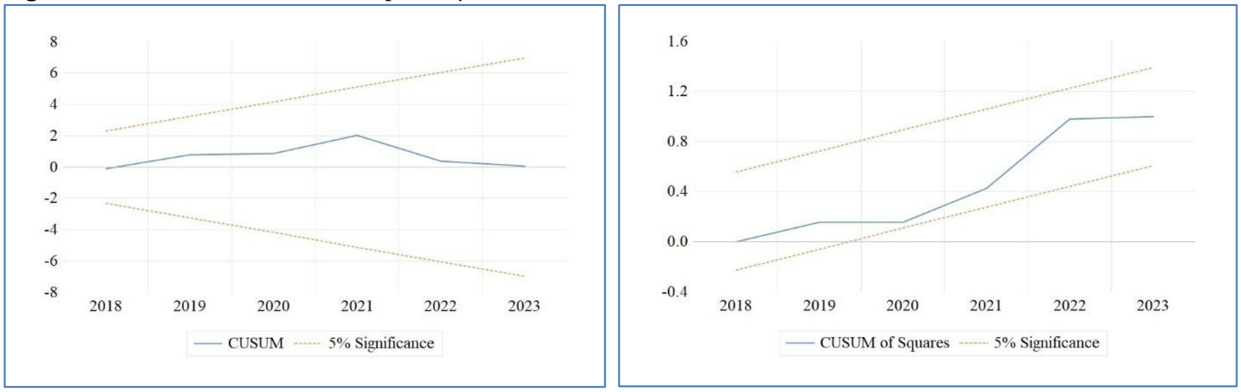
Diagnostic tests confirm the model's validity: the Breusch–Godfrey test for autocorrelation ($p = 0.2557$) and the Breusch–Pagan–Godfrey test for heteroskedasticity ($p = 0.4898$) both fail to reject the null hypothesis and the CUSUM and CUSUMSQ plots indicate model stability (Figure1).

Table 5. *Short-Run and Long-Run relationships*

Variable	Coeff.	Stand. Err.	t-Stat	P-Value
Short-run relationship				
LnLP(-1)*	-0.3651	0.0394	-9.2737	0.0001
SHIFT(-1)	0.0542	0.0049	11.0896	0.0000
GCF(-1)	-0.0306	0.0027	-11.4321	0.0000
FDI(-1)	0.1789	0.0190	9.4143	0.0001
SERV(-1)	-0.0729	0.0086	-8.4950	0.0001
D(LP(-1))	1.5486	0.1690	9.1617	0.0001
D(LP(-2))	-0.2165	0.0732	-2.9571	0.0254
D(SHIFT)	0.0483	0.0050	9.7458	0.0001
D(SHIFT(-1))	-0.0122	0.0018	-6.6410	0.0006
D(SHIFT(-2))	-0.0111	0.0013	-8.6457	0.0001
D(GCF)	0.0021	0.0017	1.2093	0.2720
D(GCF(-1))	0.0199	0.0020	10.0514	0.0001
D(GCF(-2))	0.0281	0.0025	11.1459	0.0000
D(FDI)	0.0567	0.0065	8.7429	0.0001
D(FDI(-1))	-0.0778	0.0079	-9.9015	0.0001
D(FDI(-2))	-0.0872	0.0094	-9.3028	0.0001
D(SERV)	0.0035	0.0013	2.7689	0.0325
D(SERV(-1))	0.0766	0.0086	8.8983	0.0001
D(SERV(-2))	0.0205	0.0025	8.2957	0.0002
C	5.4996	0.4975	11.0545	0.0000
Long-run relationship				
SHIFT(-1)	0.1485	0.0088	16.7842	0.0000
GCF(-1)	-0.0838	0.0040	-20.9579	0.0000
FDI(-1)	0.4900	0.0517	9.4773	0.0000
SERV(-1)	-0.1998	0.0259	-7.7219	0.0000
Model diagnostics				
Test	F-Statistic	p-Value (Prob.)		
Breusch–Godfrey Serial Correlation LM Test	1.9548	0.2557		
Breusch–Pagan–Godfrey Heteroskedasticity Test	1.1018	0.4898		

Note: D denotes the first difference $D(X_t) = X_t - X_{t-1}$

Figure 1. *CUSUM and CUSUMSQ plots of the ARDL model*



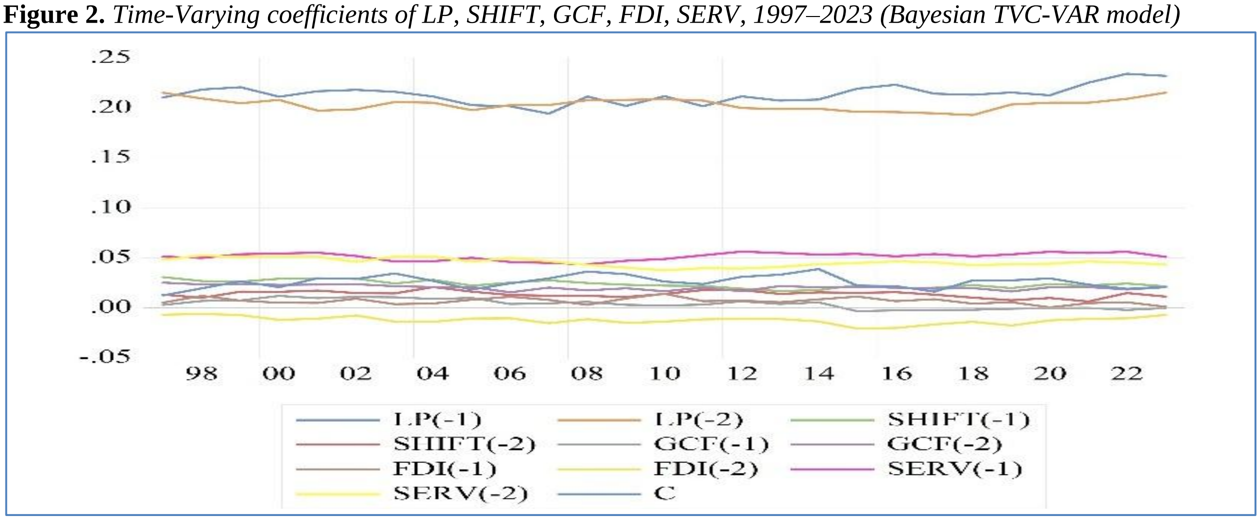
Bayesian TVC-VAR results

The Bayesian TVC-VAR model was estimated using 5,000 samples after the burn-in period, ensuring stability and convergence of the posterior distribution. The coefficients showed minimal fluctuations over time (Figure 2), indicating the model's stability. Given the dynamic priors, autocorrelation and heteroskedasticity were inherently controlled during estimation.

The results show that labor productivity (LP) lags (LP(-1) and LP(-2)) have stable positive coefficients (0.20–0.25), emphasizing the role of internal accumulation in productivity growth. SHIFT(-1) and SHIFT(-2) also show positive but modest effects, suggesting structural transformation positively influences LP, albeit to limited extent. In contrast, GCF, FDI and SERV fluctuate around zero or are slightly negative, indicating weak and unstable direct effects on labor productivity during the study period.

This finding suggests that from 1997 to 2023, internal improvements were the primary drivers of productivity growth in Vietnam, while factors like capital investment, the services sector, and foreign capital require enhanced labor quality and technological innovation to achieve more substantial effects.

Figure 2. *Time-Varying coefficients of LP, SHIFT, GCF, FDI, SERV, 1997–2023 (Bayesian TVC-VAR model)*



The empirical results from the ARDL, QQR, and Bayesian TVC-VAR models show that labor productivity in Vietnam is shaped by multiple structural factors with varying impacts over time. SHIFT consistently has a positive effect, while FDI exhibits a bidirectional relationship, contingent on the period and absorptive capacity. In contrast, SERV and GCF show unstable or negative impacts at certain times and quantiles. These findings lay the groundwork for deeper analysis of the mechanisms, productivity variations, and comparisons with existing literature, providing policy implications tailored to Vietnam's current development context.

Discussion

Effects of the transition from agriculture to industry on labor productivity

Data show a significant increase in Vietnam's structural shift since the 2000s (Figure 3), particularly from 2006 to 2016, coinciding with industrialization and economic integration. During this period, labor productivity also rose steadily, highlighting the potential of sectoral labor shifts in enhancing productivity.

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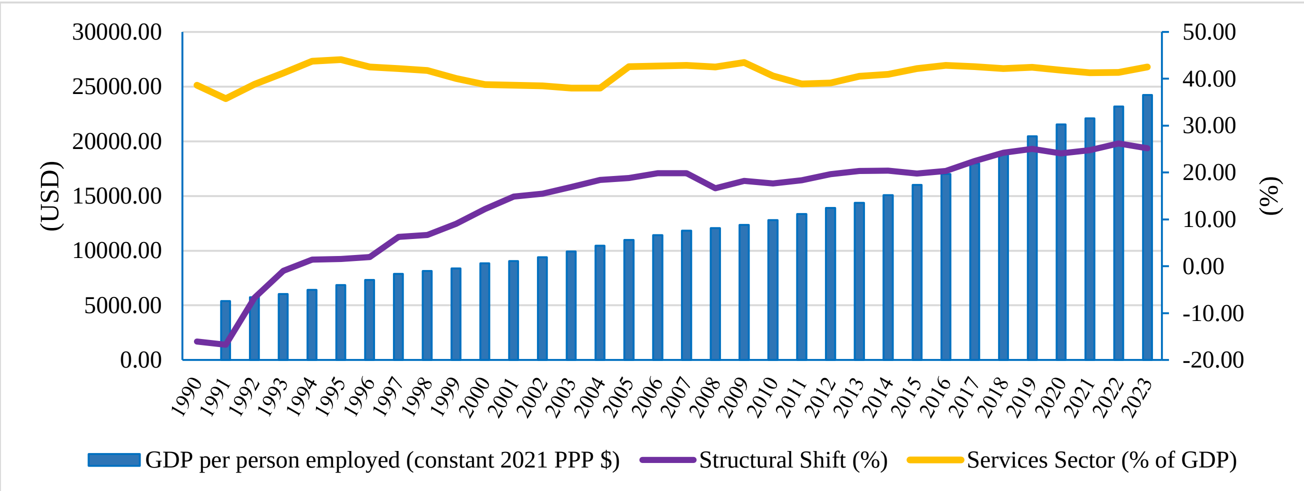
Figure 3. *Trends in LP, SHIFT, and SERV in Vietnam, 1990–2023*



The ARDL model shows that SHIFT has a strong, statistically significant positive effect on labor productivity in the long run, with a smaller positive impact in the short run. The QQR analysis (Figure 4a, 4b), using both Epanechnikov and Gaussian Kernels, reveals that SHIFT's effect is most pronounced at lower productivity quantiles (below 0.4), decreasing at medium quantiles (0.5–0.7) and narrowing at highest quantiles (0.8 and above). Both Kernels indicate consistent sign and significance, enhancing the reliability of the findings. Bayesian TVC-VAR model results also confirm that positive shocks from SHIFT lead to sustained productivity gains, particularly during periods of rapid economic restructuring (Figure 5).

Figure 4a. *Quantile Surface between LP and SHIFT, 1987–2023 (Epanechnikov Kernel)*

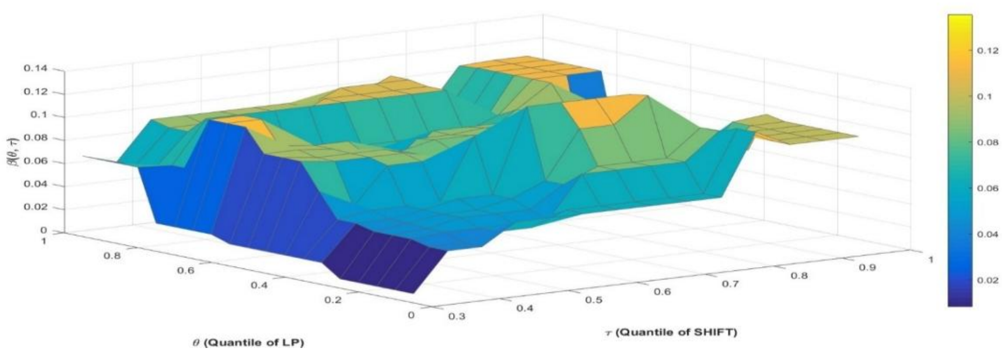


Figure 4b. *Quantile Surface between LP and SHIFT, 1987–2023 (Gaussian Kernel)*

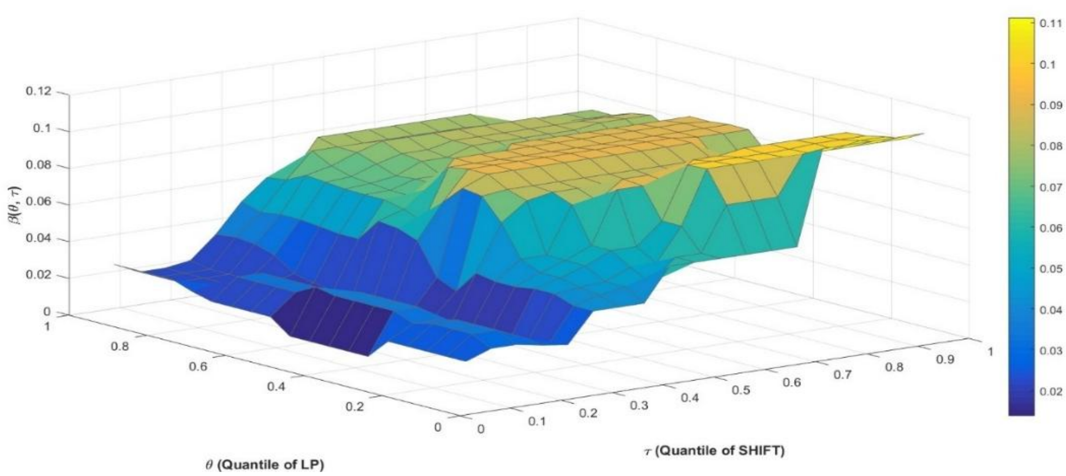


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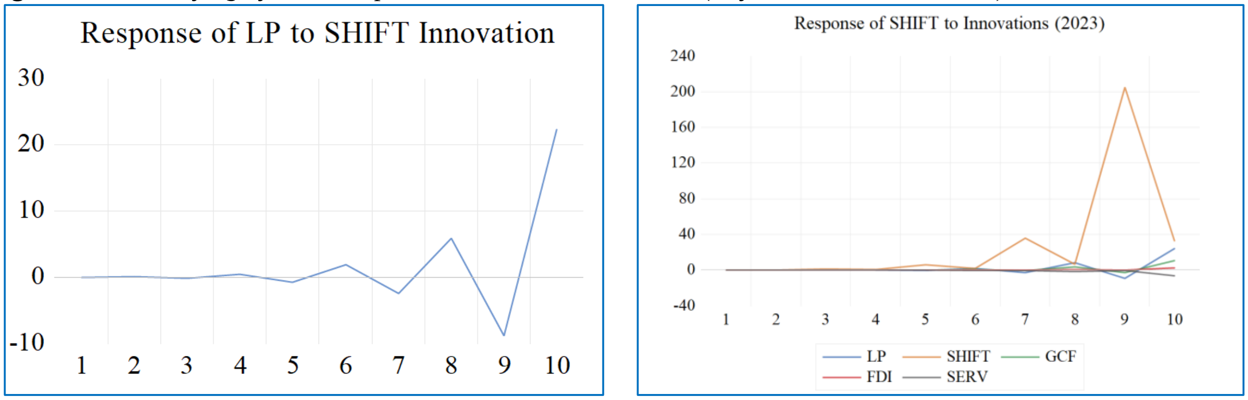
Figure 5. *Time-varying dynamic response between LP and SHIFT (Bayesian TVC-VAR Model)*



Both Vietnamese and international studies confirm the positive role of structural transformation in improving labor productivity, especially in the early and middle stages of development. In Vietnam, labor reallocation from low-productivity agriculture to industry and services has been a key driver (ILO, 2018). However, Nguyen et al. (2023) note that these benefits have slowed due to resource allocation inefficiencies and uneven labor quality. Internationally, de Vries et al. (2015) caution that short-term gains in Africa can be lost without technological innovation and improved management, while McMillan et al. (2014) emphasizes the importance of economic institutions and industrial policy. Emako et al. (2022) also demonstrate that combining FDI with sectoral restructuring is crucial for productivity growth in developing countries. These findings suggest that Vietnam's long-term productivity gains depend on integrating structural transformation with policies that enhance skills, foster innovation, and deepen integration into global value chains.

The services sector's impact on labor productivity

Statistical data show that the services sector in Vietnam's GDP has remained high, fluctuating between 38% and 43% from 1990 to 2023. However, labor productivity growth has primarily been driven by the industrial sector and structural transformation, with limited direct contribution from services.

ARDL model results indicate a significant positive long-run effect of FDI on labor productivity, confirming the role of foreign capital. QQR analysis (Figure 6a, 6b), using both Epanechnikov and Gaussian kernels, shows a strong positive impact at low and medium productivity quantiles, peaking at the (θ = 0.2, τ = 0.3) pair, with coefficients around 0.65 (Epanechnikov) and 0.61 (Gaussian). At high quantiles ($\theta \geq 0.8$), the effect weakens, reflecting limited spillover when domestic capacity is underdeveloped. The Epanechnikov kernel displays a more concentrated and steeper effect, while the Gaussian kernel shows a smoother, broader pattern. Bayesian TVC-VAR results (Figure 7) confirm a productivity boost from FDI in the early period (1995–2010), with its effect gradually declining, emphasizing the importance of absorptive capacity for sustaining long-term impacts.

Figure 6a. *Quantile surface of LP and SERV in vietnam, 1987–2023 (Epanechnikov kernel)*

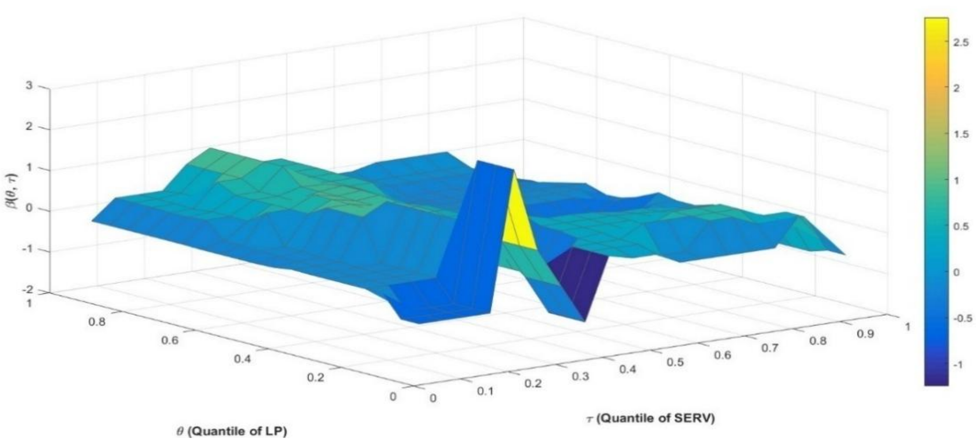


Figure 6b. *Quantile surface of LP and SERV, 1987–2023 (Gaussian kernel)*

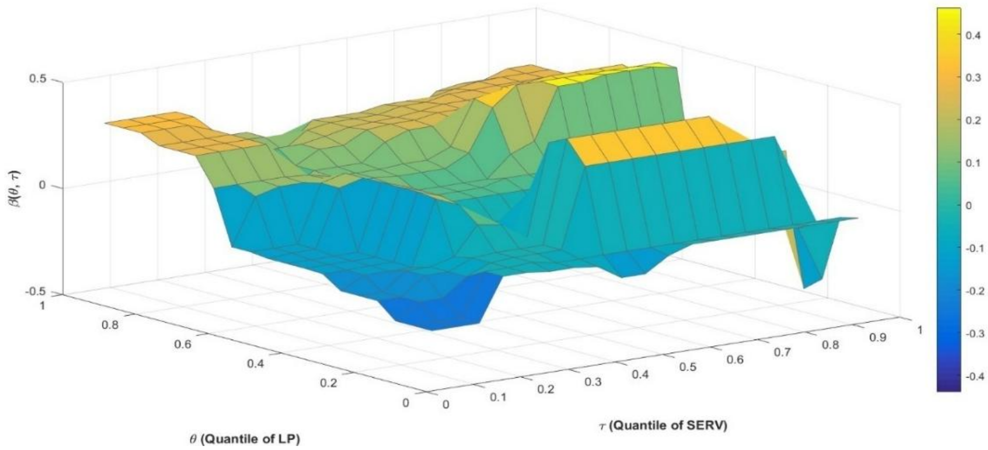
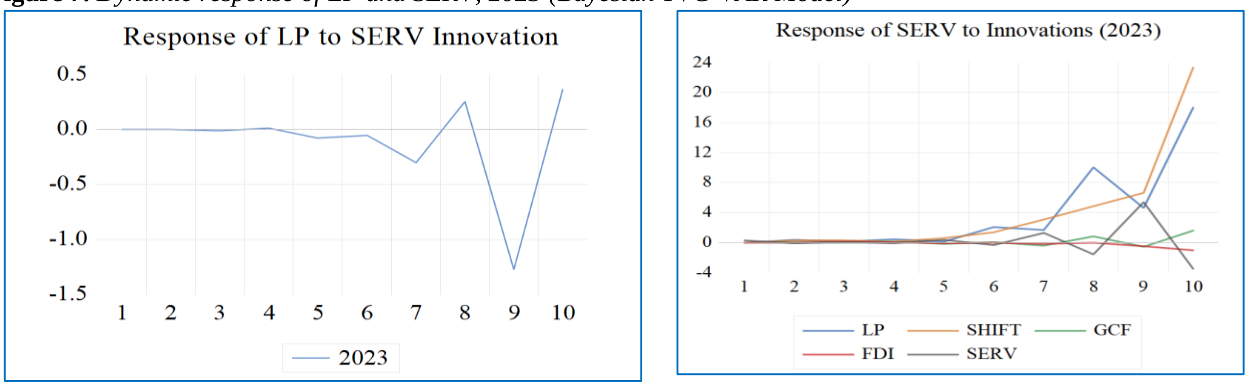


Figure 7. *Dynamic response of LP and SERV, 2023 (Bayesian TVC-VAR Model)*



Despite its large share in Vietnam's GDP, empirical results suggest that the services sector has a generally negative long run impact on labor productivity, particularly at low and medium productivity quantiles. This reflects the dominance of traditional services, like petty trade, low-cost tourism, and rudimentary transportation, which add little value. Kinfemichael (2019) argues an expanding services sector may hinder productivity unless linked to knowledge-intensive industries, while Broersma & Ark (2007) note that technology-driven services, like IT, finance, have a positive impact. In Vietnam, however, the services sector is largely informal, with microenterprises dominating and reducing efficiency (ILO, 2018). Furthermore, Tianyu et al. (2021) find that growth in India's services sector disproportionately benefits urban, wealthy consumers, exacerbating income inequality. These findings suggest that for services sector to drive productivity, Vietnam must restructure towards high-quality services and invest in soft and digital skills, alongside technological infrastructure, to support a knowledge-based economy.

Total social investment and its impact on labor productivity

Vietnam's GCF-to-GDP ratio rose sharply during 2000–2008, peaking in 2007–2008, and remained high thereafter, coinciding with steady growth in labor productivity (Figure 8). However, ARDL results reveal a negative long-run effect of GCF on productivity, implying that higher capital investment without improved efficiency may lower overall performance. QQR analysis (Figure 9a, 9b), using both Epanechnikov and Gaussian kernels, reinforces this finding, showing a pronounced negative effect at low productivity quantiles (below 0.4) that weakens at higher levels. Both QQR surfaces show a downward-sloping relationship in low-productivity ranges, particularly under the Epanechnikov. Bayesian TVC-VAR results (Figure 10) also indicate that GCF shocks initially depress productivity but recover over time, reflecting potential improvement with high-quality investment.

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Figure 8. *Trends in LP and GCF in Vietnam, 1991–2023.*

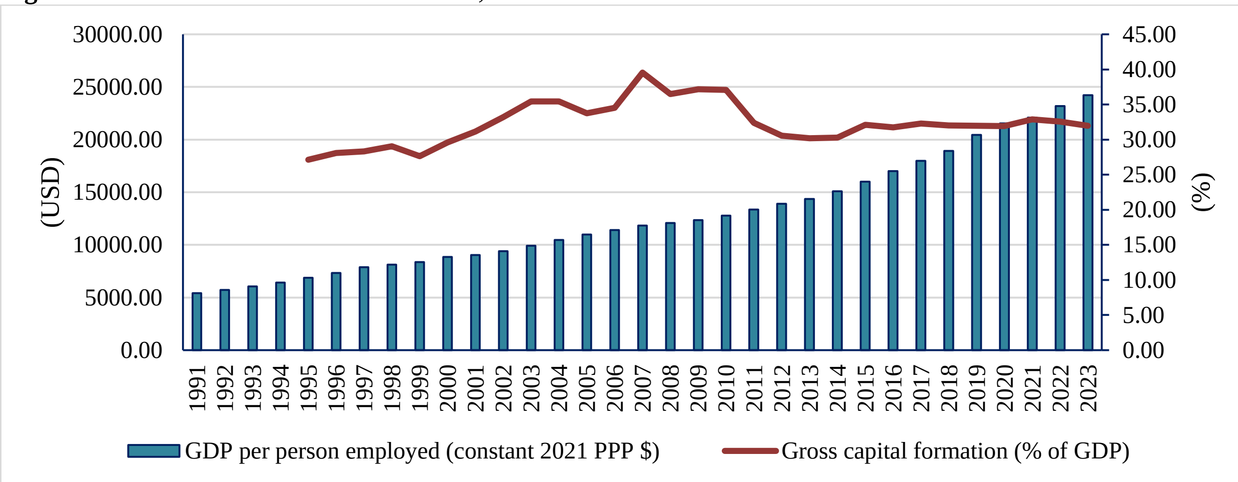


Figure 9a. *Quantile surface between LP and GCF, 1987–2023 ((Epanechnikov Kernel)*

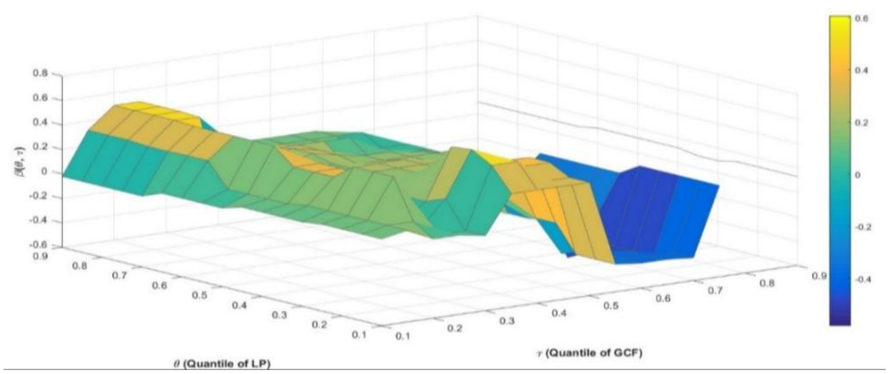


Figure 9b. *Quantile surface between LP and GCF, 1987–2023 (Gaussian Kernel).*

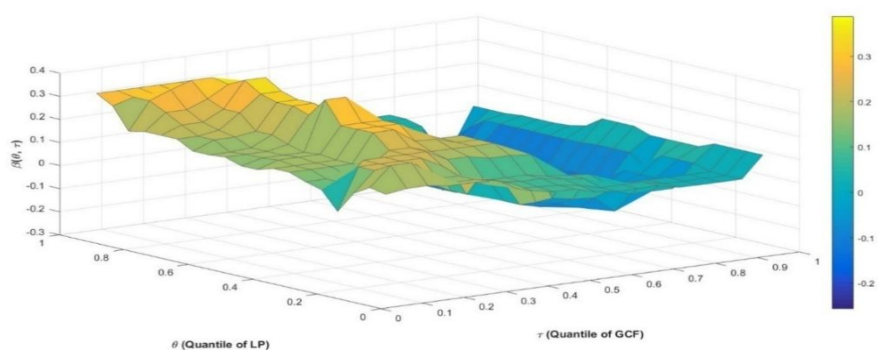
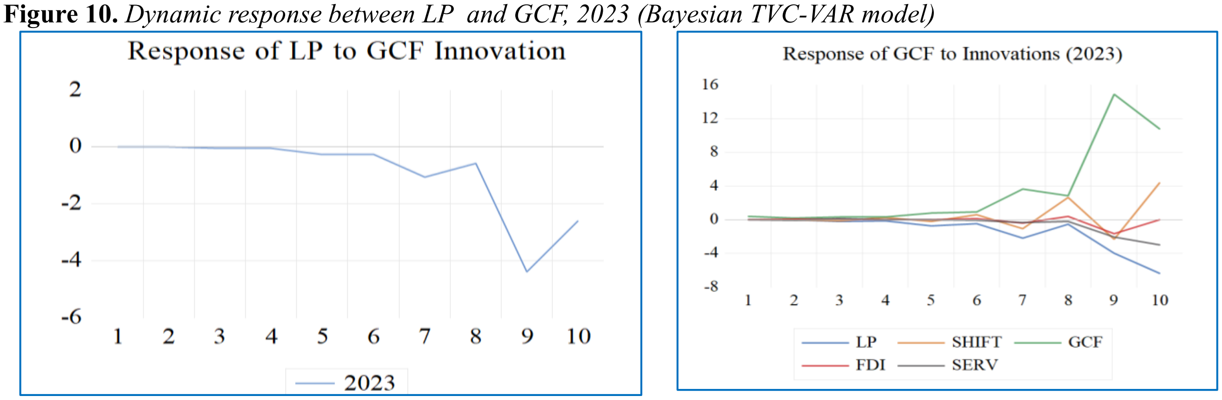


Figure 10. *Dynamic response between LP and GCF, 2023 (Bayesian TVC-VAR model)*



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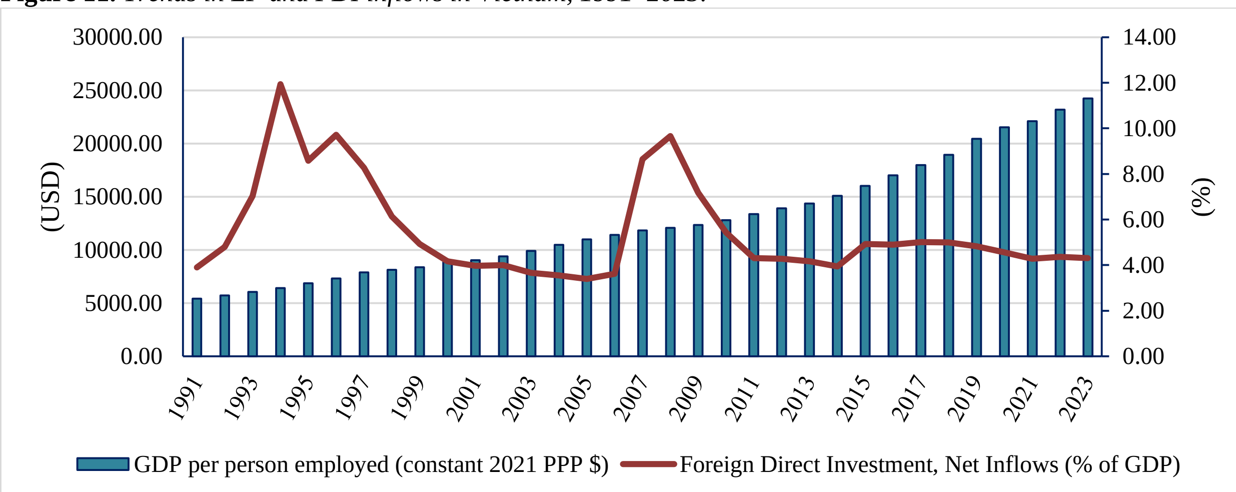
The study finds that GCF negatively impacts labor productivity in the long-run, particularly at lower productivity quantiles. This supports AlKathiri (2022), who argues that capital accumulation is only effective when paired with improvements in technical capacity and operational skills. Without enhancing technological enhancement, increased capital may lead to inefficient and resource wastage. The results also align with Sasmal & Sasmal (2023), who assert that investment is most valuable when directed toward human capital development, such as education and healthcare, which directly influence labor quality. Unlike the U.S., where productivity growth is driven by investment in intellectual assets like R&D (U. S. Bureau of Labor Statistics, 2025), Vietnam's focus remains on physical investment, with limited technological absorption capacity. This highlights the importance of not only the structure but also the content and quality of investment. The findings further corroborate Abdelgany & Saleh (2023), who highlight the positive impact of human capital, especially education and health, on labor productivity in developing countries.

FDI's impact on labor productivity

Over the past three decades, FDI has been central to Vietnam's industrialization and economic integration, with a notable increase in inflows following its WTO accession in 2007 and the subsequent trade agreements (Figure 11).

Figure 11. *Trends in LP and FDI inflows in Vietnam, 1991–2023.*



ARDL model results confirm that FDI positively impacts on labor productivity in the long run. QQR analysis (Figure 12a, 12b) using both Epanechnikov and Gaussian kernels shows that the positive effect is stronger at low and medium productivity quantiles (θ < 0.7), but weakens at higher quantiles, reflecting the limits of FDI without strong domestic capacity. The Epanechnikov kernel reveals a more concentrated impact compared to the Gaussian. Bayesian TVC-VAR results (Figure 13) support these findings, showing an initial productivity boost from FDI followed by a decline, highlighting the need for improved absorptive capacity to sustain long-term gains.

Figure 12a. *Quantile surface between LP and FDI, 1987–2023* **(***Epanechnikov Kernel)*

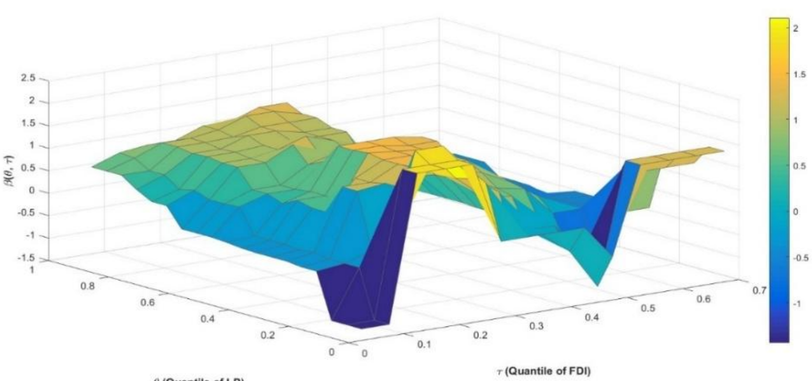


Figure 12b. *Quantile Surface between LP and FDI, 1987–2023 (Gaussian Kernel)*

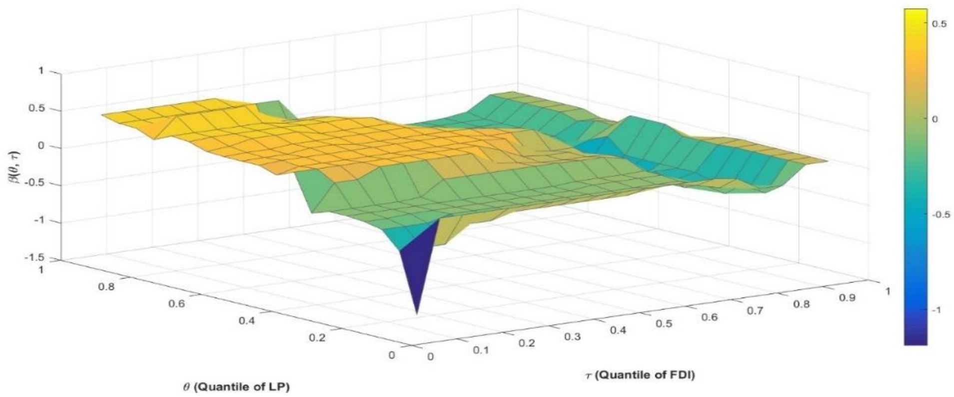
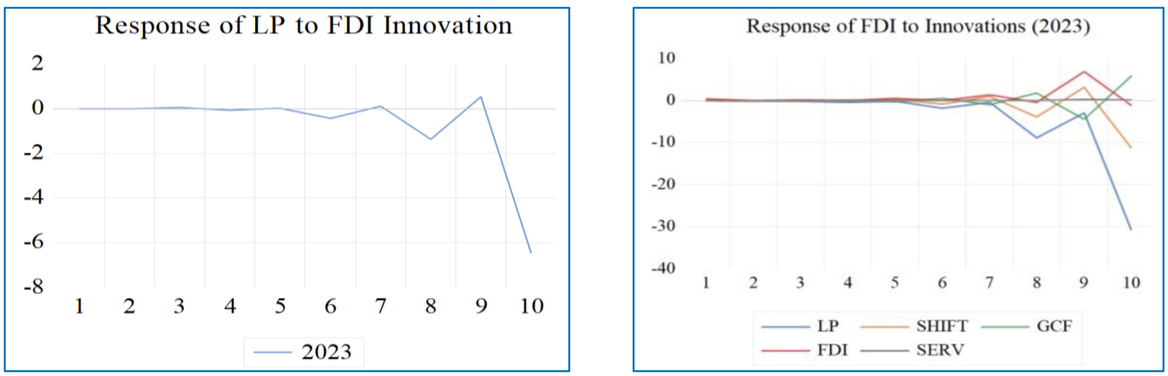


Figure 13. *Dynamic response between LP and FDI, 2023 (Bayesian TVC-VAR model)*



The study finds that FDI has a positive long-run impact on labor productivity, particularly at medium and high productivity quantiles, reflecting technology spillovers from foreign-invested enterprises to domestic firms with strong absorptive capacity. Ahn et al. (2024) confirm that greenfield FDI can generate positive backward spillovers in developing countries, provided domestic firms have sufficient technological capabilities. Similarly, Ahmed & Kialashaki (2023) highlight that spillover effectiveness in the Asia–Pacific region depends on labor force quality. A meta-analysis by Demena & van Bergeijk (2017) further confirms that FDI spillovers in developing countries are both economically and statistically significant, though influenced by research design. These results suggest that for FDI to effectively enhance productivity, complementary policies to develop human capital and strengthen technological linkages between foreign and domestic firms are essential.

Conclusion and policy implications

This study examines the impact of four key factors, structural transformation (SHIFT), gross capital formation (GCF), foreign direct investment (FDI), and the services sector (SERV) on labor productivity (LP) in Vietnam between 1990 –2023, using ARDL, QQR, and Bayesian TVC-VAR methods. The results indicate that SHIFT and FDI have significant positive effects on LP, while GCF and SERV exert negative impacts at lower productivity levels, with positive effects only observed at higher quantiles. These findings underscore the importance of structural transformation and high-quality FDI in boosting productivity, while also stressing the need to enhance capital investment efficiency and modernize the services sector to foster competitiveness and sustainable development.

Several policy implications emerge from these findings. First, structural transformation should continue to be a priority, with policies that facilitate labor movement from agriculture to manufacturing and high–value-added services, including modern vocational training aligned with the digital economy (Resolution 29-NQ/TW, 2013). Investment in high-tech industries and supporting sectors should be promoted through sectoral development programs (Decision No. 68/QD-TTg, 2010), with an emphasis on linking transformation to (Resolution 57-NQ/TW, 2024).

Second, to improve capital investment efficiency, a public investment evaluation framework should be established to ensure that investments lead to tangible productivity gains. Prioritizing digital infrastructure, smart logistics, and smart cities, along with incentives for private investment in high-tech sectors, will be crucial (Decision No. 844/QD-TTg, 2016).

Third, strengthening the economy's absorptive capacity is essential, including requiring technology transfer for new FDI projects and developing domestic supporting industries to deepen integration into global value chains (Foreign Investment

Cooperation Strategy for 2021–2030, Decision No. 667/QD-TTg, 2022). Improving workforce quality through digital skills, English proficiency, and innovation training will also be critical (High-Quality Human Resources Development Project for Industry 4.0, Project 144, 2020).

Lastly, restructuring the services sector to increase the share of knowledge- and technology-intensive services, such as finance, ICT, modern logistics, and digital healthcare, is necessary for fostering long-term productivity growth (National Strategy for Digital Economy and Digital Society Development to 2025, vision to 2030, Decision No. 411/QD-TTg, 2022). This should be accompanied by support policies for SMEs' digital transformation (the National Program to Support Enterprises' Digital Transformation, Decision No. 131/QD-TTg, 2021), and the development of an innovation startup ecosystem focused on fintech, edtech, and healthtech.

The study suggests that SHIFT, GCF, FDI, and SERV are interconnected and that a coordinated strategy is essential to maximizing policy effectiveness. FDI should be directed towards high-tech sectors, while GCF should prioritize digital infrastructure and knowledge-intensive services. Human resource development and innovation policies are crucial to transforming capital and knowledge into productivity growth across the economy.

By employing a multi-method approach with ARDL, QQR, and Bayesian TVC-VAR models, this study contributes to the literature by offering a dynamic analysis of labor productivity drivers in Vietnam. The findings clarify variations in the impacts of different factors across productivity quantiles and over time, providing nuanced policy recommendations for different stages of economic development. The integration of practical policy frameworks, such as Resolution 29-NQ/TW, Resolution 57-NQ/TW, and the FDI Strategy, further enhances the study's relevance for policymaking in Vietnam.

While the study provides valuable insights, it has limitations. The analysis of the services sector may not fully capture the rapid changes in emerging sub-sectors like digital services (van Meeteren et al., 2022; Vu & Nguyen, 2024). Additionally, the context-specific nature of findings suggests the need for cross-country comparisons. Further research could explore other factors, such as human capital, institutional quality, and technological innovation, to deepen our understanding of productivity dynamics in emerging economies.

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